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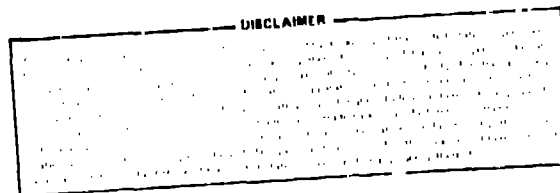
**TITLE:** APPLICATIONS OF DIGITAL IMAGE RESTORATION TO PHOTOGRAPHIC EVIDENCE

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**MASTER**

**SUBMITTED TO:** Conference on Crime Countermeasures, Carnahan House,  
Lexington, KY, May 14-16, 1980

University of California



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# APPLICATIONS OF DIGITAL IMAGE RESTORATION TO PHOTOGRAPHIC EVIDENCE\*

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**Abstract.** A review of the cepstral method of blur determination for motion blur and out-of-focus lens blur is given. A review of the maximum a posteriori restoration (MAP) method is given. The reasons for this method producing few artifacts are discussed. Results of the complete image restoration process are given.

## Introduction

Image processing and pattern recognition have been used in the field of law enforcement for some time. Perhaps the area with the longest history is automatic fingerprint analysis. One of the least used fields is that of image restoration and enhancement. Although there have been past cases where processed images were introduced as evidence, the results of such presentations were less than spectacular. Indeed in many cases this evidence was discredited. In view of past history it is important for the law enforcement community to know the capabilities and limitations of image restoration.

There are three steps in restoring any image. The first is to select an adequate mathematical model for the system that caused the degradation of the image. The second is to obtain the necessary parameters that define the selected model. The last step is to choose a method of restoration that is consistent with the model and data.

As an example, let us consider a simple linear system. This type of system can be used for low contrast film or television images. The mathematical description of this is

$$g = h \otimes f + n, \quad (1)$$

where  $f$  is the ideal, undegraded image;  
 $h$  is the space-invariant blur;  
 $n$  is signal-independent noise;  
 $g$  is the degraded recorded image;  
 $\otimes$  represents convolution.

Once we have determined that this model is adequate, there are two system parameters which must be determined -- the blur  $h$  and the noise,  $n$ .

\*Work performed under the auspices of the U.S. Department of Energy, Contract No. W7405-ENG-36.

The noise, of course, can never be known exactly. What is required by most restoration methods is the statistical characterization of the noise. The book by Andrews and Hunt<sup>1</sup> discusses several methods of obtaining this characterization.

This paper will be concerned with a method of determining the blur  $h$  from the degraded image  $g$ , and with a description of a restoration method of particular interest to the law enforcement community.

## Blur Detection

Many discussions on image restoration assume that an exact knowledge of the blur is available. In reality, such knowledge is almost never provided with the blurred photo but must be deduced. Recent work has shown<sup>2</sup> that two common blurs, motion and defocus, imbed telltale signatures in the blurred picture. Proper analysis allows the severity of these blurs to be determined.

Both motion blur and defocus blur destroy information in the photographed scene. This loss of information occurs because these blurs have zeroes in their frequency domain transfer functions. In the case of linear motion blur or an out-of-focus lens, these zeroes occur in a periodic pattern defined by  $\sin(x)/x$  or  $J_1(R)/R$  respectively. While it is sometimes possible to detect these patterns by eye in the frequency domain, the presence of noise and near-random image information usually make this approach difficult. The periodic zero pattern can be made more visible through an averaging scheme that is used in power spectrum estimation. An unusually good example of this is shown in Fig. 1, which was computed from an out-of-focus photograph.

It has been shown<sup>2</sup> that even in more difficult cases, the pattern of zeroes can be identified and used to determine blur

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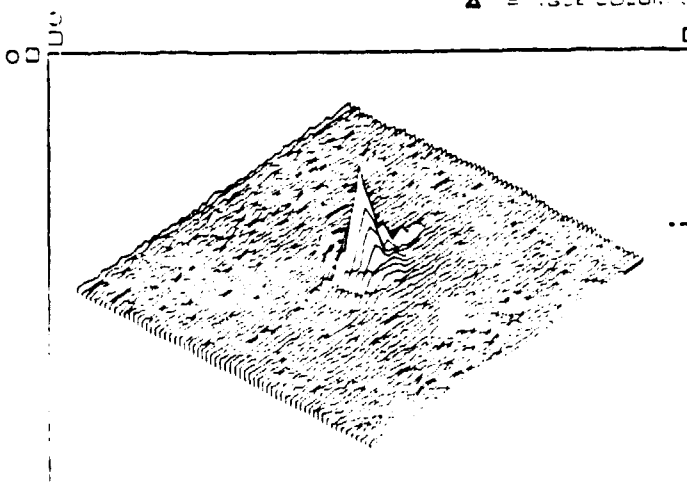


Fig. 1. Power spectrum of out-of-focus image.

severity. This is done by computing the power cepstrum of the picture. The power cepstrum is defined as the Fourier transform of the logarithm of the power spectrum. In the power cepstrum domain the circularly symmetric zero pattern of a defocus lens shows up as a ring of spikes. The zeroes of a motion blur are denoted by peaks that identify both the direction and extent of the motion.

The mathematics involved in computing the power cepstrum are straightforward. We will use the image formation model described by (1). The power spectrum for  $g$  is computed using the method proposed by Welch<sup>2,3</sup> and results in

$$\Phi_g(u,v) = \Phi_f(u,v) |H(u,v)|^2 + \Phi_n(u,v) \quad (2)$$

where  $\Phi$  denotes the power spectrum of the subscript signal and  $H$  is the Fourier transform of  $h$ . The power cepstrum is defined as

$$P_g(p,q) = F\{\log \Phi_g(u,v)\} \quad (3)$$

where  $F$  denotes the Fourier transform. It is in the power cepstrum where the telltale spikes from motion or defocus blur can be readily identified. Fig. 2. is the cepstrum of an out-of-focus picture. The radius of the ring of spikes indicates the extent of defocus.

#### Restoration

The goal of any signal restoration method is to produce an estimate of an original signal from a degraded version of that signal. The search for the criterion for determining the optimal estimate keeps a large number of signal processors off the bread lines. Among the restoration methods currently in use are maximum likelihood, maximum entropy,<sup>4,5</sup> minimum mean squared

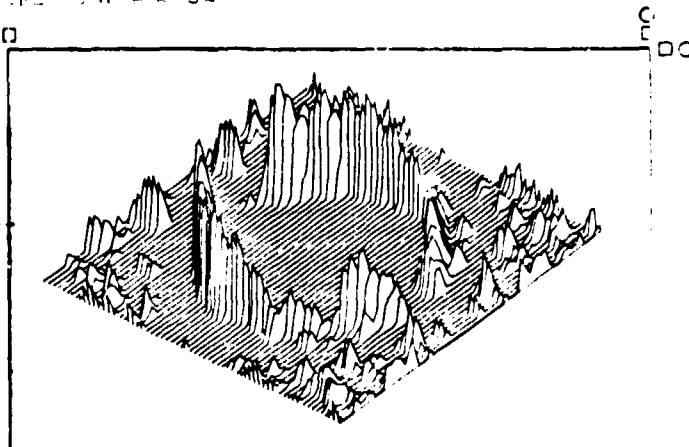


Fig. 2. Cepstrum of out-of-focus image.

error (Wiener),<sup>6</sup> power spectrum equalization (PSE),<sup>2</sup> constrained least squares deconvolution,<sup>7</sup> and maximum a posteriori (MAP) restoration.<sup>8,9</sup> Each of these schemes optimizes some function of the restored signal. Each of the methods assumes a well-defined signal degradation model (usually linear). How does the user of these methods know which one to choose for a specific application?

Of course, the answer depends upon the application. Some methods that work well for discrimination of point sources do not work well on extended objects. In order to gain some insight for choosing the appropriate restoration method, let us consider the linear image formation system (1). The general nonlinear case has been treated<sup>8,9</sup> but for illustration purposes the linear case is adequate.

The noise in the linear model plays a very important role. It is this uncertainty that prevents us from obtaining a perfect restoration. Indeed if we knew the original signal and tried to duplicate the data by passing the original through the blur, the difference would be the noise, i.e.,

$$g - h \otimes f = n \quad (4)$$

which is just (1) rewritten. From this relation we note that the residual defined by (4) should be noise. We can now define a class  $F$  of feasible solutions as:  $f_0$  is a member of  $F$  if the residual,  $g - h \otimes f_0$ , has the characteristics of the known noise. This also demonstrates the uncertainty of choosing any member of this class as the restoration.

In most cases the noise,  $n$ , is assumed uncorrelated. This should be a characteristic of the residual also. However, mathematical tests for correlation are extremely complex and for autocorrelation are unknown to these authors. A simple test is to calculate the residual and examine it by eye. In the case of images the eye is a very good estimator of significant

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correlation. If the eye can readily detect patterns in the residual, then there is significant correlation between pixels.

In the actual computation of the restored estimate, it is tractable to use only the most elementary characteristics of the noise. The one most commonly used is the variance. We will modify the definition of a feasible solution to include a larger number of members by saying a solution  $f_0$  is feasible if

$$\|g - h \odot f_0\|^2 = \|n\|^2. \quad (5)$$

Even with this extended definition we have eliminated most signals from the solution space. We have overcome a common objection that any signal can be produced from any other signal.

The fact that the condition (5) is weaker than requiring the residual to be uncorrelated can be partially overcome by using sectional processing.<sup>10</sup> The condition (5) is an average measure. If the condition is met uniformly over small local areas, the result will be a more globally stationary residual. This will give a more uncorrelated visual result.

Among the many restoration methods there are only a few which are designed to satisfy the feasibility condition (5). The one we will discuss here is maximum a posteriori (MAP) restoration. Others that also satisfy (5) are found in References 5 and 7. The MAP estimate,  $f_{MAP}$ , is the signal that maximizes the a posteriori probability  $p(f|g)$ . We assume that we know the blur,  $h$ , in (1) and the a priori probabilities  $p(g|f) = p(n)$  and  $p(f)$ . The details of the derivation of this solution are found in Reference 8. The solution is most probable in some sense. To show the fact that this solution is feasible, it is only necessary to note the equivalence of the problem to the constrained minimization problem

$$\text{minimize } \|R_f \odot (f - \bar{f})\| \quad (4)$$

$$\text{subject to } \|g - h \odot f\|^2 = \|n\|^2,$$

where  $\bar{f}$  is the mean and  $R_f$  the covariance of the distribution  $p(f)$ . This equivalence is demonstrated in Reference 9.

In actual practice it is common to choose  $\bar{f} = g$  and  $R_f = \sigma_f^2$ , a scalar. For this case the solution is the member of the class of feasible solutions which is the closest to the recorded data.

The solution method for the nonlinear image model case is iterative. The scheme is usually started with  $f_0 = g$  and moves successively toward the solution until the feasibility criterion (5) is satisfied to

within some  $\epsilon$ . Since the solution is not a single step procedure, it can be closely controlled. Other constraints, such as positivity, can be checked at each step. Because of this control on the solution, the method yields a restored signal that is remarkably free of artifacts. The MAP method has been shown to be equal to or better than other commonly used techniques<sup>11</sup> although computing costs make it unattractive in some cases.

#### Examples

To show the minimal production of artifacts in the MAP restoration we will use the examples presented in Reference 11. The degraded image (Fig. 3) was restored by two linear filters, Wiener (Fig. 4) and power

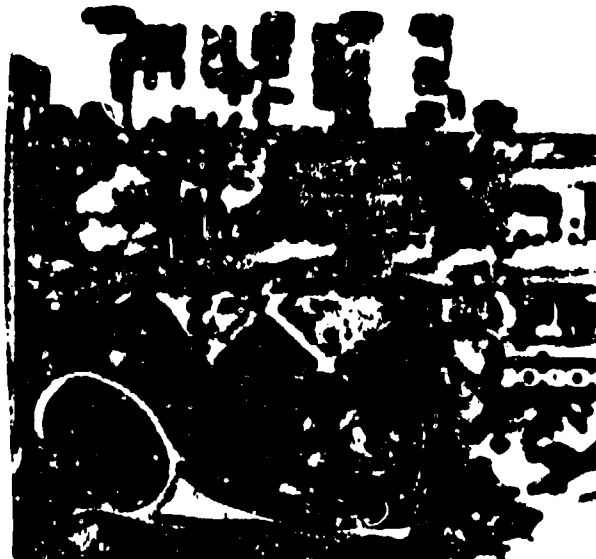


Fig. 3. Blurred harbor scene.



Fig. 4. Wiener restoration of Fig. 3.

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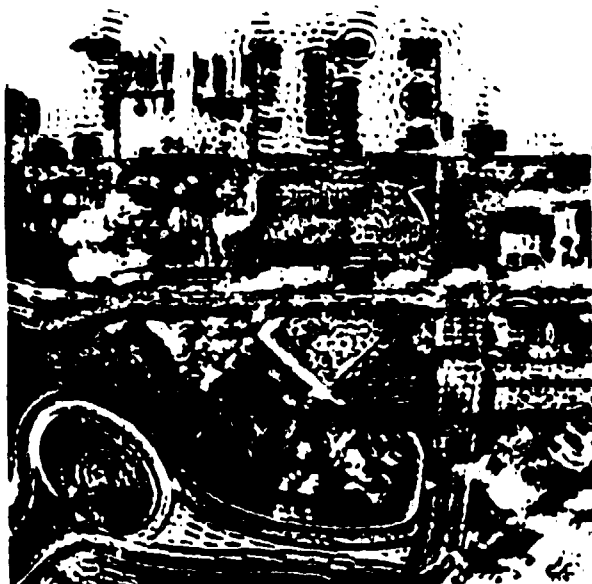


Fig. 5. PSE restoration of Fig. 3.

spectrum equalization (Fig. 5), with poor results. The MAP restoration (Fig. 6) is clearly superior because of the almost total absence of artifacts.

The use of the MAP algorithm on photographic evidence is shown in the restoration (Fig. 8) of the blurred license plate (Fig. 7). This is an actual in-camera defocus blur that could be encountered in real working conditions. The power cepstrum blur identification method described earlier in this paper was used to ascertain the extent of defocus. While the restoration in Fig. 8 is quite good, it should be pointed out that the noise was small in this case. In cases where the information



Fig. 7. Out-of-focus license plate (in-camera blur).

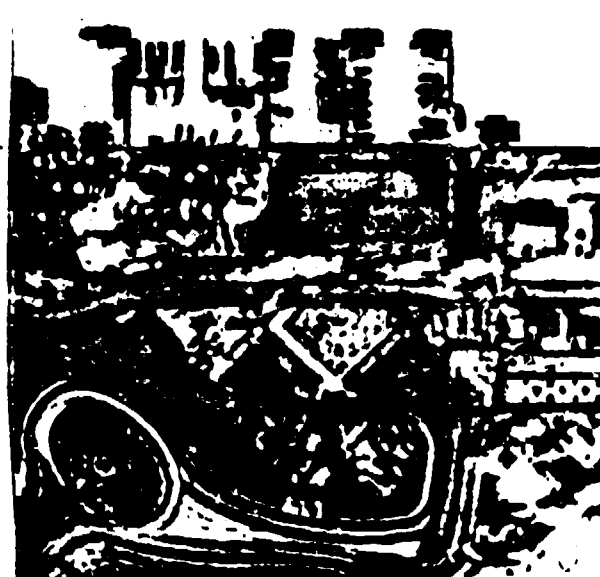


Fig. 6. MAP restoration of Fig. 3.

desired is at the film resolution limit, results cannot be nearly as good.

The MAP restoration process was applied to the Zapruder film during the investigation of the House Select Committee on Assassinations. The film was in color and thus was scanned three times through the red, green, and blue primary filters. Each of the three color scans was processed separately according to its own particular characteristics. Each emulsion had its own D log E curve, and each had a different noise level. The three restored images could be viewed separately or combined to form the color restoration.



Fig. 8. MAP restoration of Fig. 7.

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### Conclusions

We have reviewed the methods for determining the type and extent of blur directly from the degraded photograph. We have reviewed the MAP restoration method. Its use in the area of law enforcement is recommended because of its controlled behavior and its production of few artifacts. Examples were shown to sustain this recommendation.

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